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Using Locomotion Models for Estimating Walking Targets in Immersive Virtual Environments

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Abstract—Redirected Walking allows a person to explore unlimited virtual environments in a limited physical tracking space. To prevent the user from colliding with the physical boundaries of the tracking space, so-called redirection techniques are used. These techniques introduce a subtle mismatch between the user's real and virtual movement and therefore keep him inside the tracking space while at the same time they allow him to explore an unlimited virtual environment. In most cases, there is more than one redirection technique available, and steering algorithms are used to select the best one at any given time. These algorithms use an optimal control scheme to select the optimal redirection action based on a prediction of the user's future path.

In this paper, we present a novel approach for predicting a person's locomotion target. Using a set of known possible targets and models of human locomotion, this approach creates a set of expected paths and compares them to the path already traveled by the user in order to estimate the probability of the user heading for a certain target. We present a new approach for comparing two paths and evaluate its performance against three other approaches. We also compare four different ways of modeling a human's path to a target. To gather data for the comparison, a user study is conducted and the prediction performance of the different proposed approaches is discussed.

Keywords—virtual reality; redirection; human locomotion; prediction

I. INTRODUCTION

Virtual models of environments and buildings have gained great importance in engineering and architecture, but are also used in cognitive sciences as controlled environments for user studies. However, studies have shown that people using a desktop setup with mouse, keyboard and monitor do not perform as well as those who use real walking to explore the environment. Among other things, it was shown that real walking can improve the cognitive map, learning tasks and distance estimation [1], [2]. At the same time, it was shown that real walking is preferred by users over other interaction metaphors for navigating in virtual environments, like for example walking-in-place or pointing [3]. Nabyouni et al. compared real walking to using a gamepad or the Virtusphere locomotion device¹ and found that real walking was not only preferred by the users, but also performed better in terms of accuracy[4].

¹www.virtusphere.com

While the setup of a system that allows the exploration of a virtual environment with real walking is a challenge on its own due to latencies, freedom of movement, tracking and so on, the space the user can walk in is still limited by the covered area of the tracking system.

To allow the exploration of unlimited virtual environments in limited tracking spaces, Razzaque et al. [5] proposed the concept of redirected walking. Redirection tries to introduce an unnoticeable mismatch between the user's real and virtual movements in order to compress the larger virtual environment into a limited tracking space.

In recent years, a number of redirection techniques have been proposed, varying in both the kind of redirection and the break in immersion caused by the mismatch [5], [6], [7], [8]. They include a gain on rotational speeds, bending straight path segments into curves, scaling the user's forward speed and so-called resets, a forced reorientation of the user towards the center of the tracking space. It was shown by Nescher et al. [9] that using a planning algorithm to select the best techniques out of a set to be applied at any time, leads to improved performance compared to simpler approaches just using one technique. However, to do any kind of planning successfully, it is necessary to have a good estimation of the user's future behavior. The more different the possible future paths are, the more important the prediction becomes. Consider for example the situation depicted in Figure 1. The red border represents the outline of the available tracking space, the virtual walls are drawn in black. A person entering through corridor 0 has two options. If he exits through corridor 1, he should be redirected to the left. However, if he chooses corridor 2, he should be redirected to the right. In both cases, using the wrong redirection technique would lead to a collision with a wall and a reset or reorientation of the user would be necessary, causing a major break in immersion. This example should illustrate the importance of an early estimation of a person's intentions and especially the importance of decision points in the virtual environment.

II. RELATED WORK

A. Path Prediction

The need for motion prediction in redirected walking was recognized and different approaches have been proposed. Su for example extrapolate the user's past path to achieve a prediction [10]. Others are based on facing direction [6],

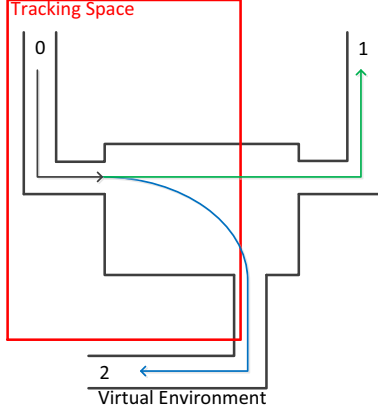


Fig. 1. Example of two possible decisions requiring redirection in opposite directions

sometimes in combination with the direction of movement [11]. Interrante et al. [7] used a weighted combination of both facing and movement directions depending on the user's speed. In this way, the facing direction is used for slow movements or standing, and the movement direction is used while the user is walking.

Since real walking in immersive environments always requires the user's head to be tracked to provide the correct view in the virtual environment, it makes sense to reuse the available data (position and facing direction) for the prediction. However, the mechanics of human gait causes oscillations in the head position and therefore the movement direction has to be smoothed over a certain time period (2 seconds for Interrante et al. [7]). This of course introduces latencies and the prediction will not be able to follow fast changes in the movement direction. This is an issue especially for redirected walking in smaller tracking spaces. Nescher et al. tried to compensate for this with a double exponential smoother, designed in such a way that it is capable of following a step function to 80% of the amplitude within 1 second [12].

B. Human Locomotion Models

However, instead of considering only the facing or moving direction, the whole path a user traveled could be considered. Since human locomotion is known to be stereotypical [13], it should be possible to compare an observed path to a number of reference trajectories from other people and, based on which one fits best, assume the target to be the same as for the reference. But the necessity to first gather experimental data on how people move in a newly created environment is impractical. Instead, we propose to use human locomotion models to create paths to compare the observed user trajectory with.

Human locomotion models are used in a wide area whenever a model for human movement is needed. Models range from simple Brownian motion approaches to handle occlusions of surveillance cameras [14] to more sophisticated models used in obstacle avoidance for robots [15] or planning robot

trajectories. Human locomotion models are usually acquired by gathering experimental data which is then used to tune model parameters such that the deviation between model and observation is minimized. This means the path generated by such a model is the expected path given a certain start and target position.

Four path models are selected for comparison which will be briefly introduced in the next section.

1) *Cirio et al.*: The model by Cirio et al. [16] is based on their observation that the distance from user to the target $\|I\|$ decreases linearly with the angle α between the target's orientation and the line connecting the target and the user, and the velocity is inversely proportional to the turning speed. Thus, they propose equation (1).

$$\frac{\|I\|}{\|\dot{I}\|} = \frac{\alpha}{\dot{\alpha}} \quad (1)$$

Using Euler integration, they update α , and together with limits on the human walking and turning speed, they obtain an updated position. The position is updated in this way until the target is reached.

2) *Arechavaleta et al.*: The second model is by Arechavaleta et al. [17]. It is based on the fact that human paths like many other movements adhere to certain optimality criteria. They use equation (2) for the system's dynamics and cost function (3) that has to be minimized by the path to a target.

$$\begin{pmatrix} \dot{x}_T \\ \dot{y}_T \\ \dot{\varphi} \\ \dot{\kappa} \end{pmatrix} = \begin{pmatrix} \cos \varphi \\ \sin \varphi \\ \kappa_T \\ 0 \end{pmatrix} u_1 + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} u_2 \quad (2)$$

$$J = \frac{1}{2} \int_0^T \langle u(\tau), u(\tau) \rangle d\tau \quad (3)$$

3) *Fink et al.*: Fink et al. [18] use a steering model based on (4), where φ is the user's heading, ψ_g the goal's orientation, d_g the distance to the goal, and $b = 3.25$, $k_g = 7.50$, $c_1 = 0.40$ and $c_2 = 0.04$.

$$\ddot{\varphi} = -b\dot{\varphi} - k_g(\varphi - \psi_g)(e^{-c_1 d_g} + c_2) \quad (4)$$

Like the model by Fink et al., they update the position and orientation until the target is reached.

4) *Graph*: The planning of redirection is time-critical and can already take a long time, if the number of available actions is high [9]. In addition, the generation of a model path will cost additional time, especially if an optimization is involved. To see if an simplistic, but very fast approach is still viable, a graph representation using linear path segments is included. While it is of course not a realistic model for human locomotion, it is the simplest and fastest possible approach, and in case the performance is satisfactory, there would be no need for more complicated models. For more complex environments, these kinds of models can be found in robotics literature, but for the small, obstacle-free environments used

here the model path is represented by a straight line connecting start and goal.

These models allow creating a path given a start and a target location, and while the start position is of course the position where the person started their path from, the location for the targets decision is not that clear. Anything a person could want to walk to can potentially be a target. This includes of course objects that the user can interact with, images and locations that offer a nice view, but also key locations of the environment's spatial configuration such as doors or hallways. In this paper, we assume that the locations of the targets are known. In a real application, this has to be either tagged by hand or considered when building the environment, or recognized automatically in the environment for example based on a floor plan.

III. COMPARING PATHS

The path models presented in the previous chapter allow generating a possible path of a human from a given start position to a certain target. Assuming that the model is accurate, the path the user actually travels to the chosen target should be similar to the one the model generated in the beginning. If we had a suitable measure for the similarity that can be used while the user is still walking, it would be possible to decide to which model the observed path is most likely belonging to and thus which one is the most likely target. In the following chapter, we will present three such similarity measures and a comparison method.

A. Cost Function

Previous research has shown that many human movements follow certain optimality criteria [19], [20]. They use a cost function J that is minimized by the trajectory a human moves on. Based on this, we propose a novel comparison method that uses such a cost function to compare paths based on their cost by estimating the amount of movement wasted by deviating from the optimal path.

The exact definition of J varies between authors, in the case of Mombauer et al. for example the function (5) is used, where a is the acceleration, ψ is the angle between the current facing direction and the direction to the target, and T the overall time. But they all optimize towards a short path while at the same time minimizing the changes in forward acceleration and curvature. This corresponds to a smooth path without quick changes in direction and no unnecessary changes in velocity.

$$J(\mathcal{P}) = T + 1.2 \int_0^T \dot{a}_{forw}^2 dt + 1.7 \int_0^T \dot{a}_{rot}^2 dt + 5.2 \int_0^T \psi^2 dt \quad (5)$$

Bellman's Principle of Optimality is a necessary condition for optimality and it states that any part of a solution of an optimization problem itself is the optimal solution of the associated sub-problem. In the context of human paths, this means that any optimal path can be split and the solution for the two parts is the same as for the combined case (Figure 2). In this case, (6) follows where \mathcal{P}_M is a path generated by a model, J is a cost function associated with human path

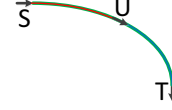


Fig. 2. Selecting a position u on the optimal path from S to T (green) and calculating the solutions for S to U (red) and U to T (blue) results in the same overall path because of Bellman's Principle of Optimality

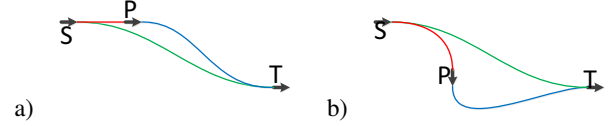


Fig. 3. Model path $\mathcal{P}_M(S, T)$ from start S to target T (green), path $\mathcal{P}_{real}(S, P)$ traveled by user U (red) and new model path $\mathcal{P}_M(P, T)$ from U to T (blue). In case a), the deviations are small and J_{loss} will also be small. In case b), the observed path deviates far from the model and J_{loss} will be large.

planning, s and t are the path's start and end points, and $u \in \mathcal{P}_M(s, t)$ is any point on the original path.

$$J(\mathcal{P}_M(s, t)) = J(\mathcal{P}_M(s, u)) + J(\mathcal{P}_M(u, t)) \quad (6)$$

Since $\mathcal{P}_M(s, t)$ is optimal, (7) will hold for $\forall p \in \mathbb{R}^2$. This means that every path diverging from the optimal model will have higher cost, even if the user follows the optimal path from now on.

$$J(\mathcal{P}_M(s, t)) \leq J(\mathcal{P}_M(s, p)) + J(\mathcal{P}_M(p, t)) \quad (7)$$

We use this to define J_{loss} as in (8), where \mathcal{P}_{real} is the user's recorded path and p is his or her current position. J_{loss} is zero, if and only if \mathcal{P}_M is a perfect model, since J has to be nonnegative to be a valid cost function. This means that J_{loss} is a measure for the user's deviation from the optimal path and that the increase in path cost is measured through the cost function J . Since J is a cost function validated with experimental data, the increase in cost is correctly weighted between changes in length and curvature. In a more informal way, J_{loss} can be thought of as a measure for "wasted" movement on a path towards a certain target. It will for example increase only a little if the user deviates from the path (Figure 3a), however it would increase rapidly if the user turns away from or moves past the target (Figure 3b).

$$J_{loss} = J(\mathcal{P}_M(s, t)) - (J(\mathcal{P}_{real}(s, p)) + J(\mathcal{P}_M(p, t))) \quad (8)$$

B. Dynamic Time Warping

Dynamic Time Warping is a method for comparing sequences of temporal data originally published by Sakoe and Chiba [21]. It is widely used in classifying time varying patterns such as speech, video or movement data.

In general, it uses a distance measure $d(s, t)$ between the symbols s and t and then, given two sequences S and T of length M resp. N , finds a sequence of indices i, j of length L such that $\sum_{k=1}^L d(S(i(k)), T(j(k)))$ is minimal. This is usually done using a dynamic programming algorithm and there can be restrictions on $i(k), j(k)$ with respect to $i(k-1), j(k-1)$ depending on the application.

Since Dynamic Time Warping has been used successfully to deal with varying talking speeds and gesture recognition, it should also be well suited for dealing with speed differences between walkers and models.

Because our work is concerned with human locomotion paths, the sequences S and T are sequences of points in \mathbb{R}^2 . Therefore, we choose d to be the euclidean L2 norm. Furthermore, all points in the sequences have to be connected and only forward steps are allowed, therefore $0 \leq i(k) - i(k-1) \leq 1$ and $0 \leq j(k) - j(k-1) \leq 1$. The overall distance from the comparison is then divided by the length of the path to compensate for varying path lengths.

Since the model covers the whole path from the starting location to the end, and the recorded path is only partially complete, they cannot be compared directly. Instead, only the beginning of the model path is used, such that it has the same length as the recorded path.

C. Minimal Distance

Minimal distance finds the closest point in the reference path T for each point of the test path S and sums up the distances. The sum is divided by the path length because otherwise $MD(S, T)$ would also depend on the length of the path.

$$MD(S, T) = \sum_{i=1}^M \min_{t \in T} (|S(i), t|) / M \quad (9)$$

D. Double Exponential Smoothed Direction

This approach for target estimation was originally proposed by Nescher et al. [12]. The underlying idea is to use a user's facing or movement direction to infer the intended target. However, due to gait-induced oscillations this direction varies over the course of the step which disturbs the prediction. To overcome this problem, Nescher et al. proposed to use a double exponential smoother to smoothen the oscillations while keeping the latency lower than with a moving average filter of comparable performance. Equations (10) and (11) from [12] describe the smoothing of the movement direction $\vec{\omega}$ with $\alpha = 0.004$, $\beta = 0.004$ and the output \vec{s} .

$$\vec{s}_t = \alpha \vec{\omega}_t + (1 - \alpha)(\vec{s}_{t-1} + \vec{b}_{t-1}) \quad (10)$$

$$\vec{b}_t = \beta(\vec{s}_t - \vec{s}_{t-1}) + (1 - \beta) \vec{b}_{t-1} \quad (11)$$

Any direction-based approach can use either direction of movement or facing direction, since sensors for gaze direction or torso orientation are not commonly available. While it is known that gaze can be an indication for intention in other fields, a user can also look at something without the intention

to walk there. Therefore, using the movement direction might have advantages, but the robustness depends on the walking speed and it becomes useless once the user stands still. In the future, a speed dependent blending between walking and facing direction might be interesting, but this is outside of the scope of this paper.

In order to estimate the target, the angular deviation between the smoothed movement direction \vec{s} and the direct connections between the user's position and the targets are compared.

IV. MAKING DECISIONS

Independent of model and comparison method, the estimator gives one scalar value d_i per target i for every position sample provided by the tracking system. On its own, this vector is not useful for planning; instead, either a binary decision or a probability distribution over all targets is needed. For n given targets, there are two ways of approaching this problem. In the first approach, every target can be analyzed on its own and it can be decided if it is still a possible target or not. This could be done for example based on experimental data describing how much humans typically deviate from the optimal path. The alternative is to approach it as a classification problem. In this case, the whole n -dimensional vector is used and we try to either assign the sample to one of the targets or estimate the probability of belonging to each individual target.

However in this paper, we limit ourselves to two targets and therefore we will present a decision scheme in two dimensions. The easiest way to do this would be to simply assume the target with the smaller distance value to be the correct one. However, there are some problems with this approach. First, a small error could lead to a wrong decision; second, slight changes in the path, for example caused by gait, can cause the estimation to alternate between the two targets which in turn would have an adverse effect on the planning algorithm's performance. Instead, we use a sigmoid function (12) to map the difference in distance between the two targets to the range $[0, 1]$ for target 1. For target 2, 13 is used. The sigmoid function should be 0.5 for $d_1 = d_2$, but the slope can be set dependent on the comparison method by setting c appropriately.

$$P_1 = \frac{1}{1 + e^{-c(d_2 - d_1)}} \quad (12)$$

$$P_2 = \frac{1}{1 + e^{-c(d_1 - d_2)}} = 1 - P_1 \quad (13)$$

V. EXPERIMENT

In order to test the proposed prediction method and compare the models and methods, an experiment was designed. The goal was to offer participants two targets and have them walk to one of them. An empty room with two exits was shown to the participants and they were instructed to pick one of them and then walk towards it. They were deliberately not given any additional task such as a search or fetch task to avoid situations where they change their target during locomotion because they suddenly spot their target. While we are aware that this does not represent the most realistic use case, it provides clear and

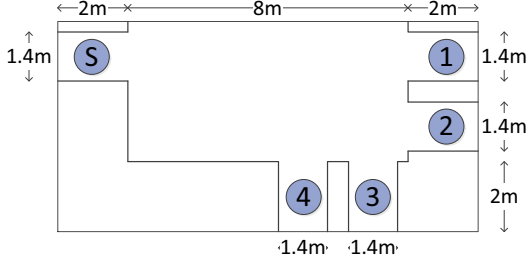


Fig. 4. Layout of the virtual environment with start location S and targets 1 through 4. Only two exits were visible at any given time.

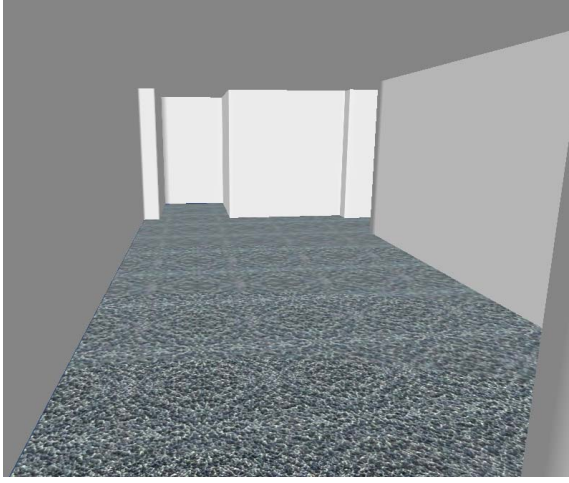


Fig. 5. The image shows a view from the starting location towards the two exits in condition 1.

uncontaminated data for an initial evaluation. At the same time, we decided to leave the choice of the target to the participants.

After they left the room through the exit they were instructed to return to their starting position, and once they reach the start position, a room with a new layout was shown. Four different locations for the exits were tested resulting in a total of six combinations, but not all combinations are included in the evaluation. The reasons for this is that in certain situations the targets are extremely close together and trajectories are very similar which means, that on the one hand an accurate prediction is difficult, but on the other hand is also not that important when using it for planning redirection. Figure 4 shows the location of all targets in the room, the used conditions are listed in table I.

The experiment was designed as a balanced block design with three repetitions, which gives a total of 18 paths per participant. The user study was conducted with our virtual reality setup, the used tracking system is an Intersense IS-

1200 attached to an Oculus DK2 head-mounted display². Both are connected to an HP Elitebook 8560w running Windows 7. The virtual environments are created in Unity3D³. 18 people were recruited from the student body (13 male, 5 female). The average age was 23.7 years (standard deviation 2.3 years), average height was 1.77 meters (standard deviation 0.09). Nobody had prior experience with our setup.

Some trials had to be excluded for technical reasons or because participants did not complete the task correctly. For some trials it looked like participants changed the target half way through, but no trials were excluded for this reason, because in some of these cases it was unclear if he actually changed his mind or just did not walk according to the model, in which case he should of course not be excluded.

This resulted in a total of 304 trajectories out of which 162 belonged to conditions 1 to 3 and were used in the evaluation. Each recorded path contains position and orientation information at 180 Hz. However, for the evaluation only every 20th sample was evaluated, resulting in a frequency of 9 Hz. For the prediction, the first sample is used as a starting point and the target's position is used as the end point for the model path.

VI. RESULTS

There are two main metrics to compare the performance of the different combinations of models and estimation approaches presented previously. The first one is the percentage of correct estimations. However, it is possible that the estimations for the two targets are very close together and when just assuming the more likely one to be the correct answer, even a small error might lead to a wrong decision or an alternating result. To avoid this situation, we allow samples to be assigned to the "undecided" category, meaning they are assigned to neither of the two targets. This introduces the second metric, the percentage of samples that are classified. We only accept a decision if $P_i \geq 0.6$ for any target i . If none of the targets is above this value, the sample is classified as undecided. Unless otherwise noted, all results only include the three main conditions and $p < 0.05$ is used as a significance level.

As a first step, the sigmoid function defined in section IV, that is used for the decision, needs to be tuned. For this, the first 3 paths of every participant are used and a range of sigmoid functions is tested. Figure 6 shows the resulting ratio of the number of correctly classified samples to the overall number of classified samples ($= R_{CC}$) and ratio of the number of classified samples to the total number of recorded samples ($= R_{CT}$) for all the model/comparison combinations and conditions included in the evaluation. It can be seen that there is a trade-off between maximum correctness ($R_{CC} \rightarrow 1$) and a high number of classified samples ($R_{CT} \rightarrow 1$), which was expected. It can also be seen that certain combinations perform strictly better than others, most notably the combination of the model by Arechavaleta et al. and the cost based estimation. For an easier comparison, all sigmoid parameters are chosen such that $R_{CT} = 0.85$.

Figure 8 shows all paths recorded for condition 2 with the model by Arechavaleta et al. and the cost based estimator. It

TABLE I. CONDITIONS USED IN THE EXPERIMENT

Condition	Targets
1	1 & 2
2	1 & 3
3	1 & 4

²www.oculus.com

³www.unity3d.com

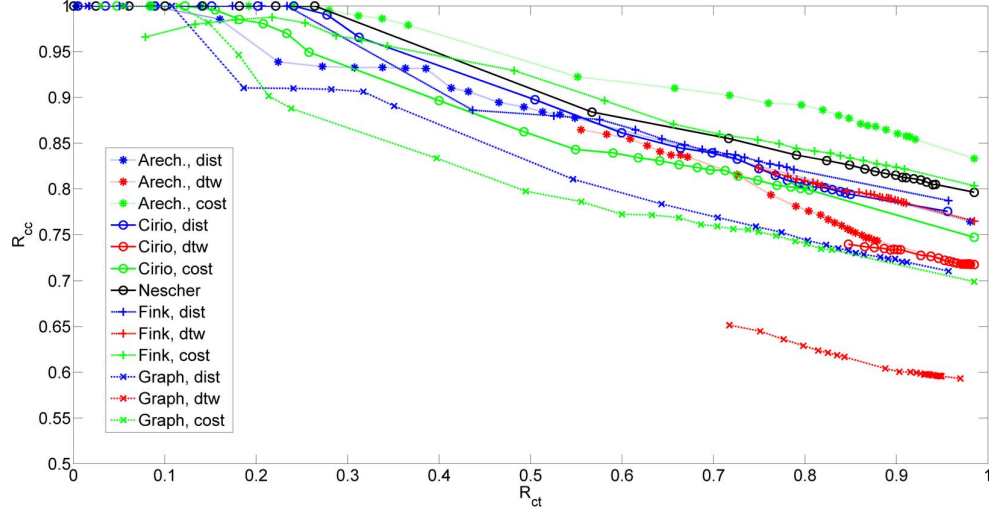


Fig. 6. The plot shows the R_{CT} and R_{CC} values for all tested model/classifier combinations using the sigmoid function defined in (12) with different values of c .

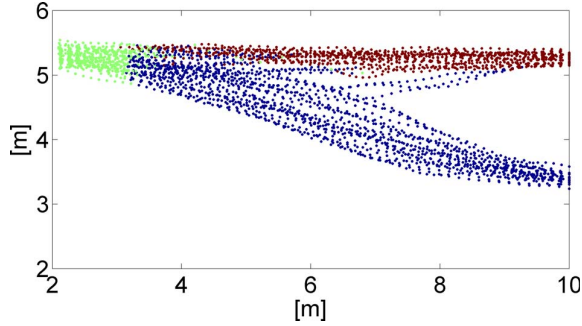


Fig. 7. Paths recorded for condition 1 for the combination Fink/DTW. Red and blue points are assigned to the respective targets, green samples are undecided

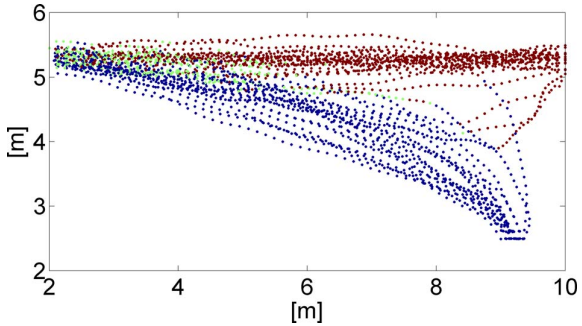


Fig. 8. Paths recorded for condition 2 for the combination Arechavaleta/Cost. Red and blue points are assigned to the respective targets, green samples are undecided

TABLE II. NUMBER OF CORRECT SAMPLES OVER NUMBER OF CLASSIFIED SAMPLES

	Arechavaleta	Cirio	Fink	Graph
Dist	0.84	0.85	0.85	0.80
DTW	0.78	0.79	0.79	0.74
Cost	0.91	0.84	0.85	0.86
Nescher	0.87			

TABLE III. STANDARD DEVIATION OF THE CORRECT TO CLASSIFIED RATIO BETWEEN USERS

	Arechavaleta	Cirio	Fink	Graph
Dist	0.133	0.095	0.097	0.085
DTW	0.086	0.093	0.116	0.084
Cost	0.055	0.078	0.089	0.082
Nescher	0.063			

can be seen that the undecided classification occurs mainly at the beginning and in the zone where the two path-groups overlap. In Figure 7 an example of an estimator using DTW and Fink's locomotion model can be seen. Almost all samples in the beginning are classified as "undecided", in contrast to the cost based estimator, but afterwards all samples are assigned to a target either correctly or incorrectly.

In terms of the correct to classified ratio, the cost based estimators are significantly better than both DTW and Distance based estimators. Distance is significantly better than DTW. Over all comparison methods, Fink et al's model performs significantly better than all other models, while the graph model is significantly worse than all others. There is no significant difference between Cirio's and Arechavaleta's models.

TABLE IV. PERCENTAGE OF TIMES TARGET 1 WAS PICKED DEPENDING ON THE CONDITION.

Condition	Target 1
1	51.0%
2	58.9%
3	35.3%

TABLE V. PERCENTAGE OF TIMES WHERE A GIVEN TARGET WAS REPEATED (ONLY TRIALS WHERE THIS WAS POSSIBLE WERE INCLUDED)

Target	Repeated in
1	24.0%
2	22.2%
3	53.3%
4	31.6%
Total	32.6%

A. Target statistics

The presented approach allows for the use of a prior probability if there is additional information about the typical behavior in this specific environment available. Since the participants had the choice of selecting their target, we also evaluated the frequency of choice for each target and condition. Table IV shows the percentage of times in which target 1 was selected compared to the respective other target. While it was not always possible to select the same target as in the previous run, 32.6% of times participants selected the same target again if it was. The results per target are listed in table V.

B. Model performance

To evaluate the performance of the models themselves, we use the same comparison metrics, but only compare the correct model path with the complete recorded path. For DTW, distance and cost function, the model by Arechavaleta is significantly closer to the observed paths than the others and while there is no significant difference between Fink's and Cirio's model, the graph model achieves a significantly worse match.

C. Performance over time

Since the walking task is performed over a certain time, the performance of the estimation will also change over time. At the same time, the estimation should be available as early as possible to have more time for redirecting the user if necessary. Figure 10 shows the performance along the paths. For easy comparison, the paths were all segmented into 20 parts of equal length. The performance increases over time, both in the number of classified and the number of correct samples. The cost based estimators show a higher R_{CT} early on, but the increase is slower compared to the distance and DTW estimators, which start at zero but increase very quickly at around 10% progress.

D. User performance

An important factor of the performance is the general applicability of the model and comparison method. Figure 9 shows the performance per user for one of the model and estimation combinations. While there is a relatively large number of outliers, it should be noted that the median marked by the horizontal red line is 1.0 for most users and very close for the rest. This means that even though there are some outliers that performed poorly, the majority of all paths still has very good or perfect performance.

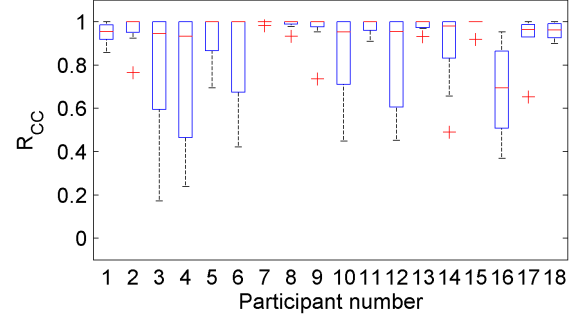


Fig. 9. Performance per user with the model by Fink et al. and the cost based estimation method.

VII. DISCUSSION

The experiment conducted for this paper demonstrated the feasibility of target prediction using human locomotion models. The more complex models performed significantly better than the simple connecting line, but they come with longer computation times, especially in the case of the model by Arechavaleta et al. However, the models used allow for different sizes of their respective update steps which is directly related to the run time of the model itself and also to the number of points in the final model and therefore the run time for the comparison. Especially for the Dynamic Time Warping approach, the run time could be significantly reduced by limiting the number of points in the model and recorded path, as well as putting some limitations on the matching. The model by Arechavaleta et al. uses optimization and therefore the run time is directly influenced by the abort criteria and the initial conditions.

The cost based comparison method proved to perform best, followed by the Dynamic Time Warping comparison. Especially the movement direction based approach exhibited the expected problem of always predicting target 1 first, independently of the real target. Here, a comparison against the expected direction based on a model might perform better, but in this case it loses its advantage of being simpler than the other methods and not needing any locomotion model.

While the prediction did work for all the people participating in our experiment, it is possible that for some people the model might just not describe their behavior accurately. However, it is important to keep in mind that even a prediction that appears to be wrong considering the final target, might have been right at the time before the participant changed his mind. Because the deviation is very small in some cases, these trials were not excluded but in future experiments it might be worth considering to ask the participants to announce their target before they start to walk.

VIII. CONCLUSION

In this paper, we presented a novel approach for predicting a person's intended locomotion target. The novel method of comparing an observed path to model paths using a cost function has outperformed all comparison methods including both a direction based approach and the classic Dynamic Time Warping technique.

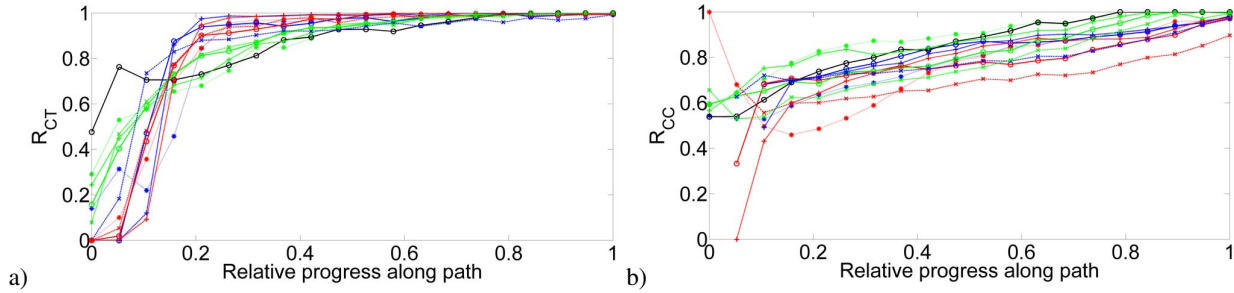


Fig. 10. a) Classified to total ratio over time. b) Correct to classified ratio over time. For the legend, please refer to Figure 6.

At the same time, the model by Arechavaleta et al. outperformed all other models while the simple graph model was outperformed by the other models.

Currently, we assume that the potential targets are known. However, for future applications it would be an advantage to automatically recognize decision points in the environment. Furthermore, the experiment presented in this paper had a very simple layout. In reality, a user can not only walk from one starting location to a goal. Instead, it is possible that he continues to a next target once he reached a waypoint, or he stops half way to look around for example. Also changing visibility will have an influence on paths and both static and mobile obstacles need to be included in the path modeling.

Using eye tracking could be an alternative for or addition to the presented method by allowing for an initial estimate even earlier during the path. However, to justify the additional complexity and increased cost, the performance improvement needs to be significant.

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